Robust Tightly Coupled GNSS/INS Estimation for Navigation in Challenging Scenarios

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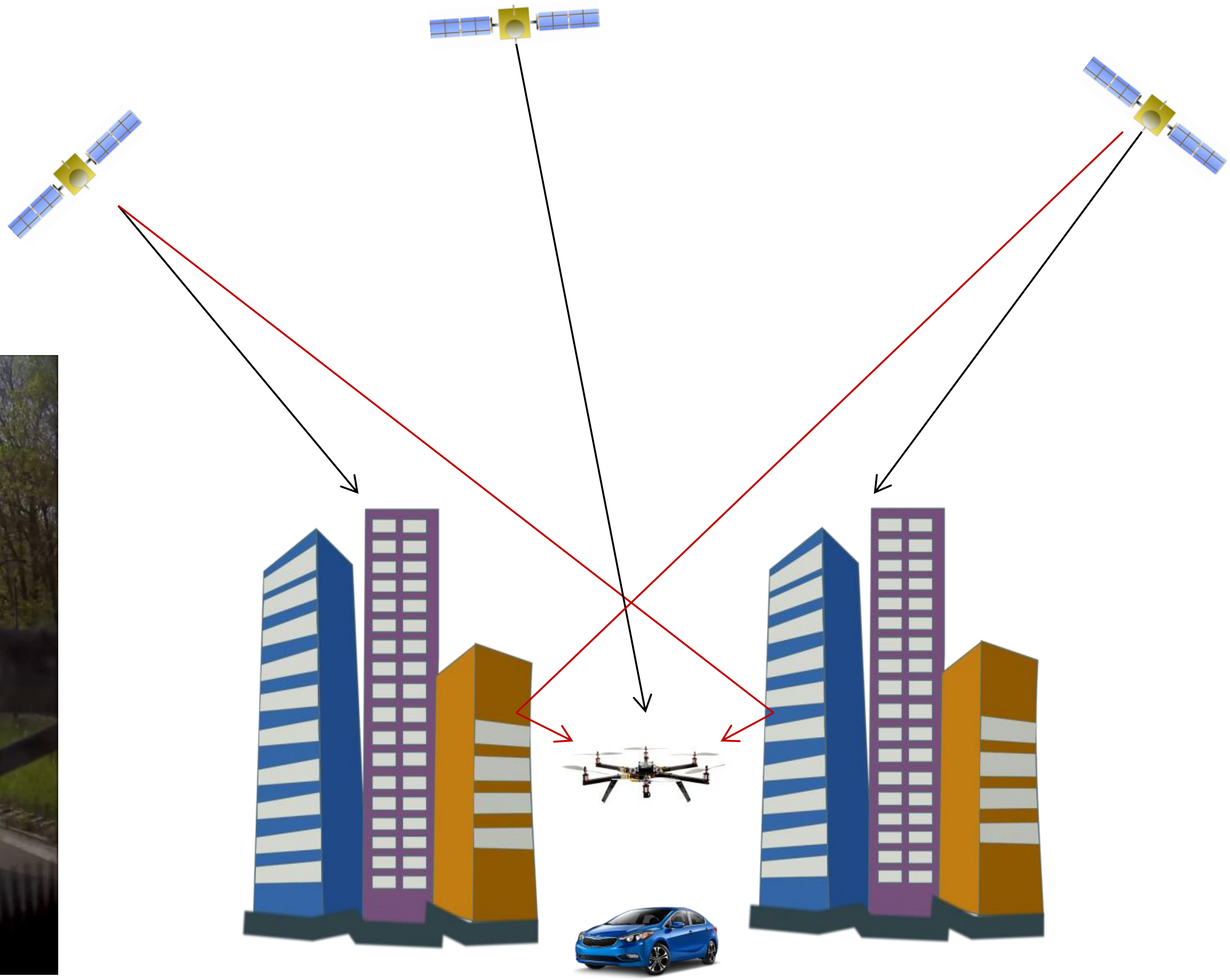
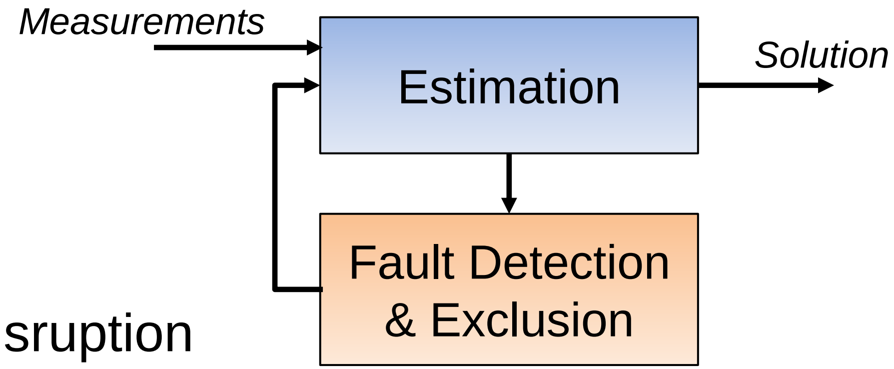
Motivation

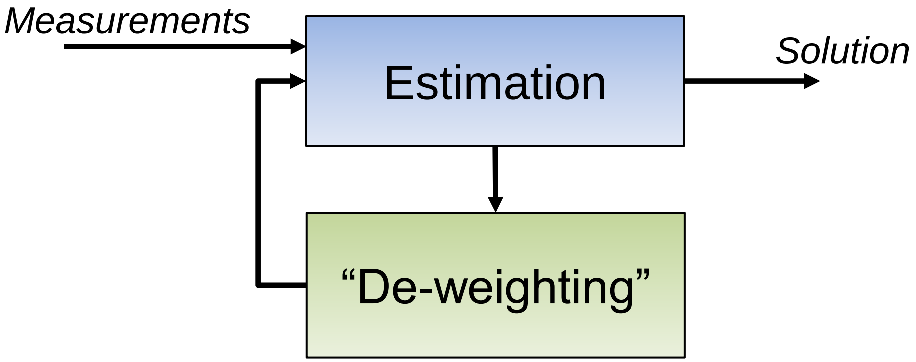
- **Challenging Scenarios for GNSS:**
  - Limited Visibility
  - High multipath
  - Multiple NLOS signals



Introduction



- Most resilient user algorithms are designed for Civil Aviation:
  - Open-sky assumption
  - Resilient against GNSS system/ wide-area faults
  - Linear Estimation + Fault detection and Exclusion
  - Under multiple fault, exclusion may fail leading to service disruption



- Alternative solution: Robust Estimator
  - No prior assumption required
  - No hard decisions
  - Getting some attention from GNSS community

  - **Problem: Need of sufficient data to perform well**
  - **Question: How can the “redundancy” of inertial sensor help?**

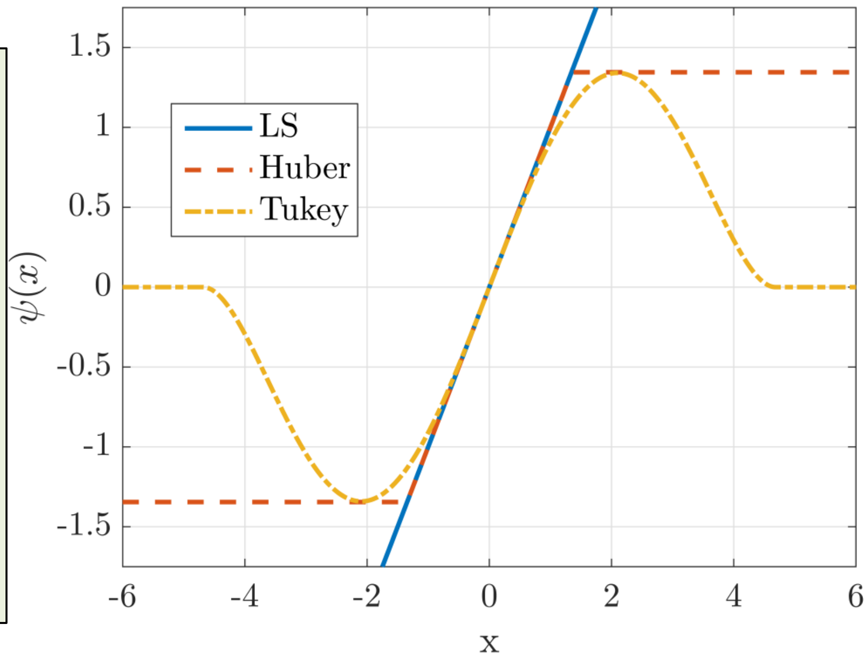
Robust M Estimation

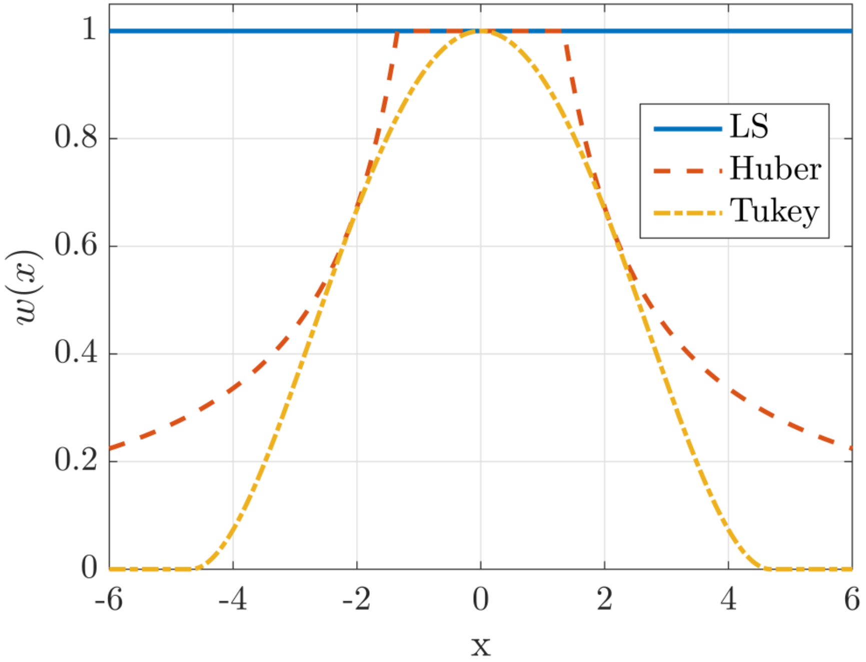
- **Least – Squares (LS)**

$$\hat{\mathbf{x}}_{\mathrm{LS}} = \min_{\mathbf{x}} \sum_i r_i^2\left(\mathbf{x}\right)$$

- **Robust Estimator**

$$\hat{\mathbf{x}}_{\mathrm{M}} = \min_{\mathbf{x}} \sum_i \rho\left(\frac{r_i\left(\mathbf{x}\right)}{\sigma_i}\right)$$





$$\hat{\mathbf{x}}_{\mathrm{M}} = \min_{\mathbf{x}} \sum_i \bar{r}_i^2 \cdot w\left(\bar{r}_i\right)$$

Solved by Iterative Reweighting Least-Squares (IRLS)

- Influence function:

$$\sum_i \Psi\left(\frac{r_i}{\sigma_i}\right)\frac{\partial r_i}{\partial \mathbf{x}} = 0$$

- Weighting function:

$$w(\bar{r}^i) = \Psi(\bar{r}^i)/\bar{r}^i$$

GNSS / INS Error-state Extended Kalman Filter (EKF)

- 16 States:

$$\mathbf{x} = \begin{pmatrix} \delta\boldsymbol{\psi} & \delta\mathbf{v} & \delta\mathbf{p} & \mathbf{b}_a & \mathbf{b}_g & b_u \end{pmatrix}^T$$

- Prediction:

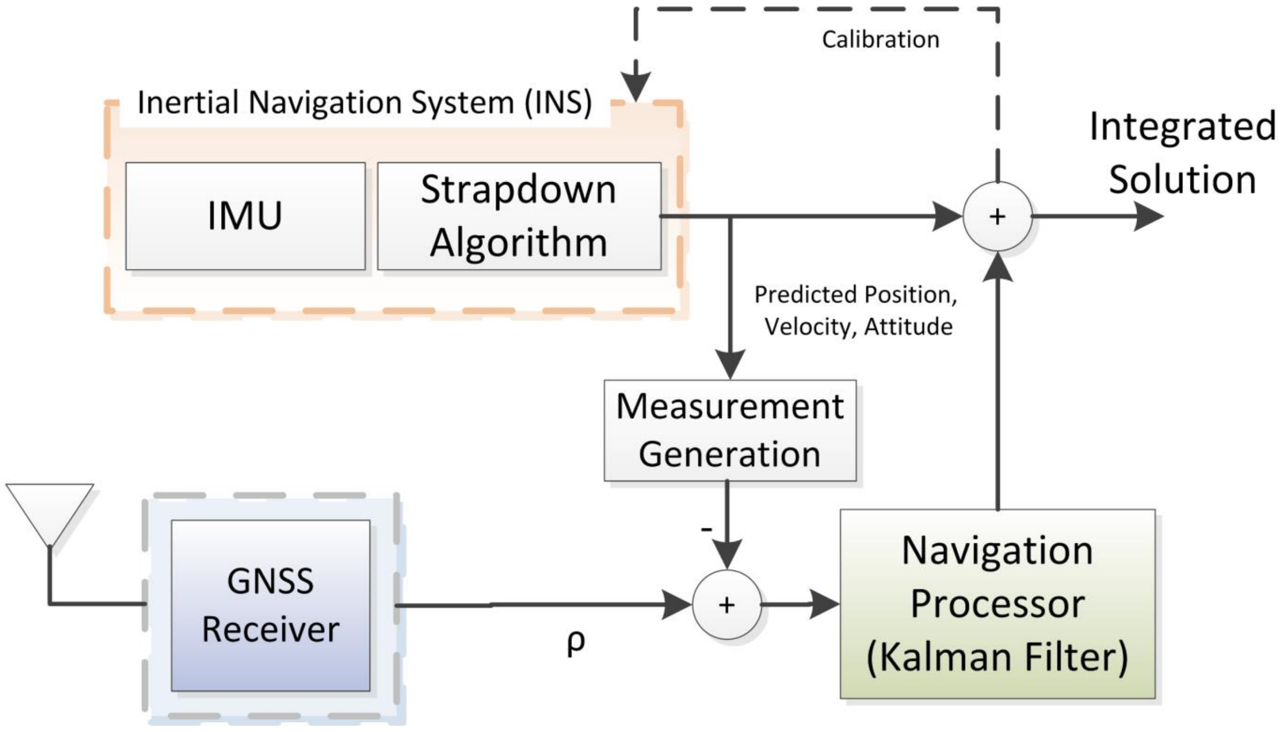
$$\mathbf{x}_k^- = \mathbf{\Phi}_k \mathbf{x}_{k-1}^+ + \mathbf{G}_k \mathbf{w}_{k-1}$$

$$\mathbf{\Phi}_k \approx \mathbf{I} + \mathbf{F}_k \Delta t$$

- Update:

$$\mathbf{x}_k^+ = \mathbf{x}_k^- + \mathbf{K}_k \left(\mathbf{z}_k - \mathbf{h}(\mathbf{x}_k^-) \right)$$

As Least-Squares problem



GNSS / INS Robust EKF Estimation

- Update Step as Weighted Least-squares:

$$\underbrace{\begin{bmatrix} \mathbf{z}_k \\ \mathbf{x}_k^- \end{bmatrix}}_{\tilde{\mathbf{z}}_k} = \underbrace{\begin{bmatrix} \mathbf{H}_k \\ \mathbf{I} \end{bmatrix}}_{\tilde{\mathbf{H}}_k} \mathbf{x}_k + \underbrace{\begin{bmatrix} \mathbf{v}_k \\ \boldsymbol{\nu}_k^- \end{bmatrix}}_{\tilde{\mathbf{v}}_k}$$

→ KF measurement equation

→ KF prediction as a measurement

- Extended Measurement Equation: $\tilde{\mathbf{z}}_k = \tilde{\mathbf{H}}_k \mathbf{x}_k + \tilde{\mathbf{v}}_k$

$$Cov[\tilde{\mathbf{v}}_k] = \begin{bmatrix} \mathbf{R}_k & \mathbf{0} \\ \mathbf{0} & \mathbf{P}_k^- \end{bmatrix} = \tilde{\mathbf{R}}_k = \mathbf{L}_k \mathbf{L}_k^T$$

- Pre-whitening of measurement: $\underbrace{\mathbf{L}_k^{-1}\tilde{\mathbf{z}}_k}_{\bar{\mathbf{z}}_k} = \underbrace{\mathbf{L}_k^{-1}\tilde{\mathbf{H}}_k}_{\bar{\mathbf{H}}_k} \mathbf{x}_k + \underbrace{\mathbf{L}_k^{-1}\tilde{\mathbf{v}}_k}_{\bar{\mathbf{v}}_k}$

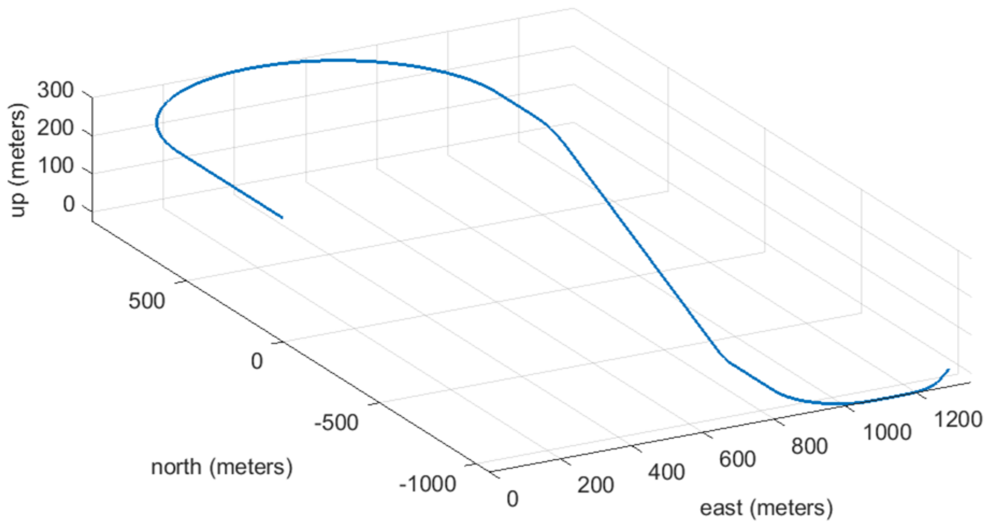
- Solve Iterative Reweighted Least Squares with Huber M estimation:

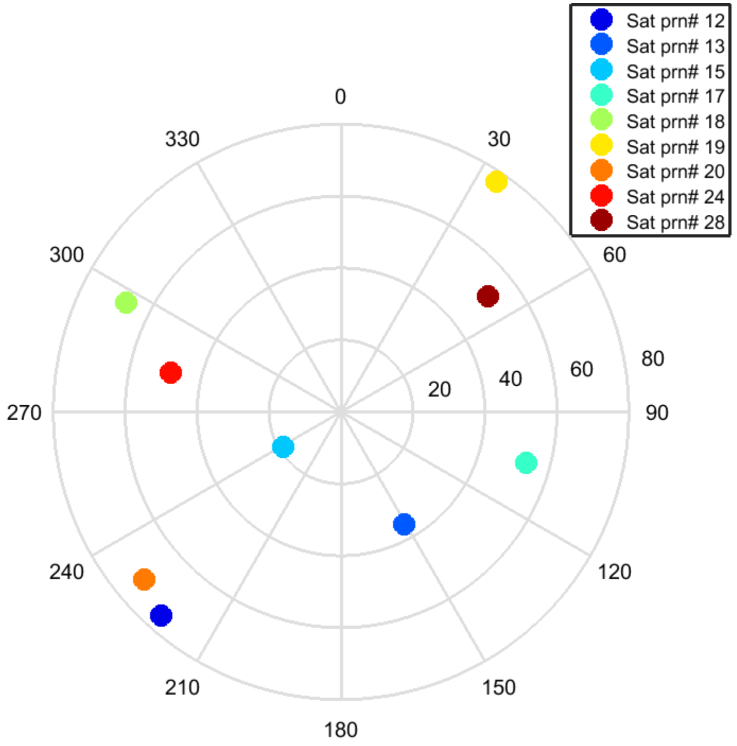
$$\hat{\mathbf{x}}_k^i = \left(\bar{\mathbf{H}}_k^T \mathbf{W}^{i-1} \bar{\mathbf{H}}_k\right)^{-1} \bar{\mathbf{H}}_k^T \mathbf{W}^{i-1} \bar{\mathbf{z}}_k$$

$$w_{\mathrm{Huber}}(\bar{r}) = \begin{cases} 1 & \text{if } |\bar{r}| \leq k \\ \frac{k}{|\bar{r}|} & \text{if } |\bar{r}| > k \end{cases}$$

Results: Simulation Scenario

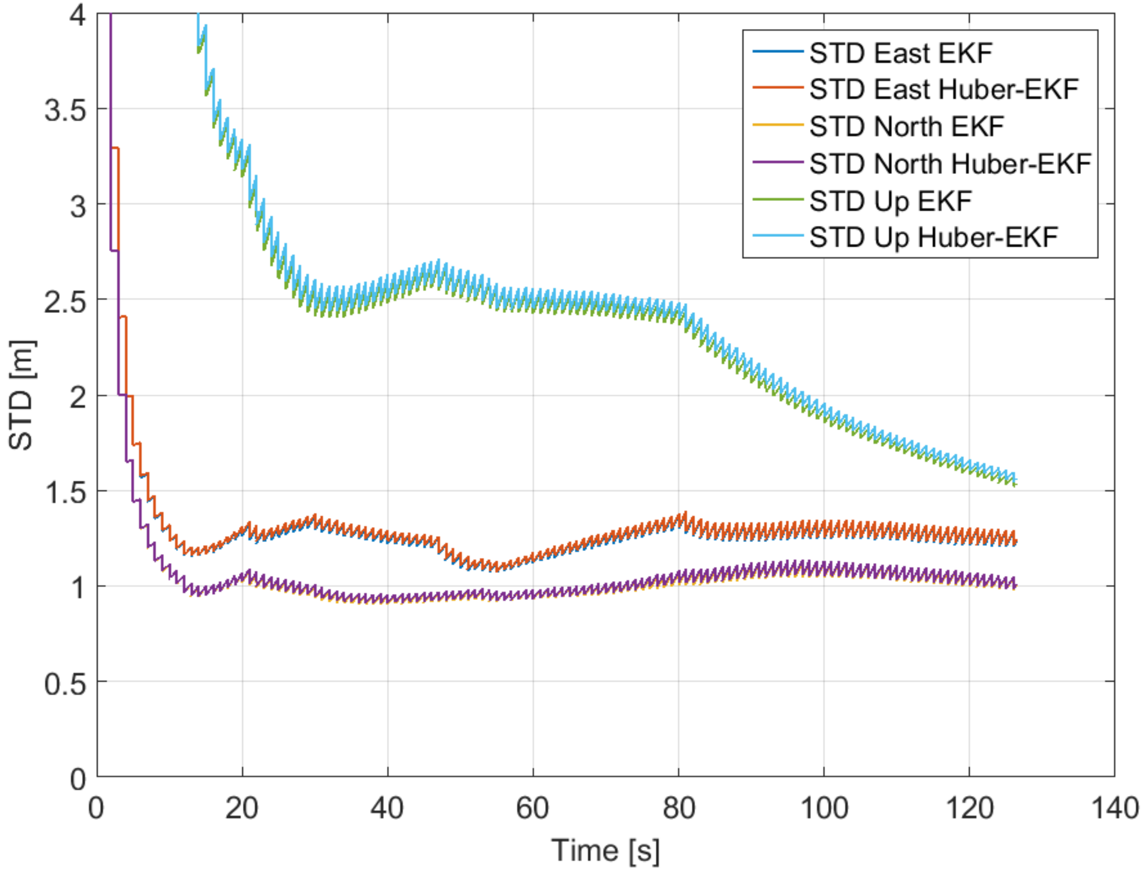
- Simulated trajectory and GPS constellation

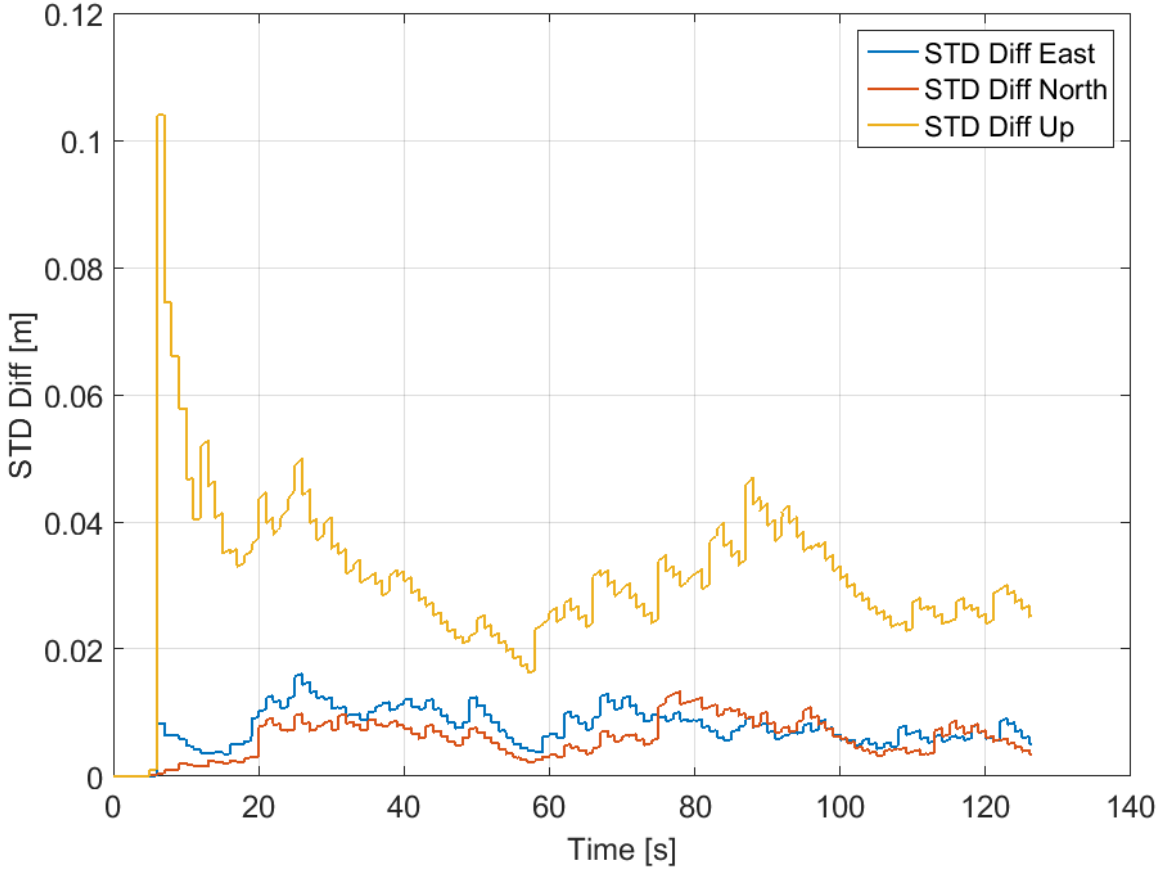




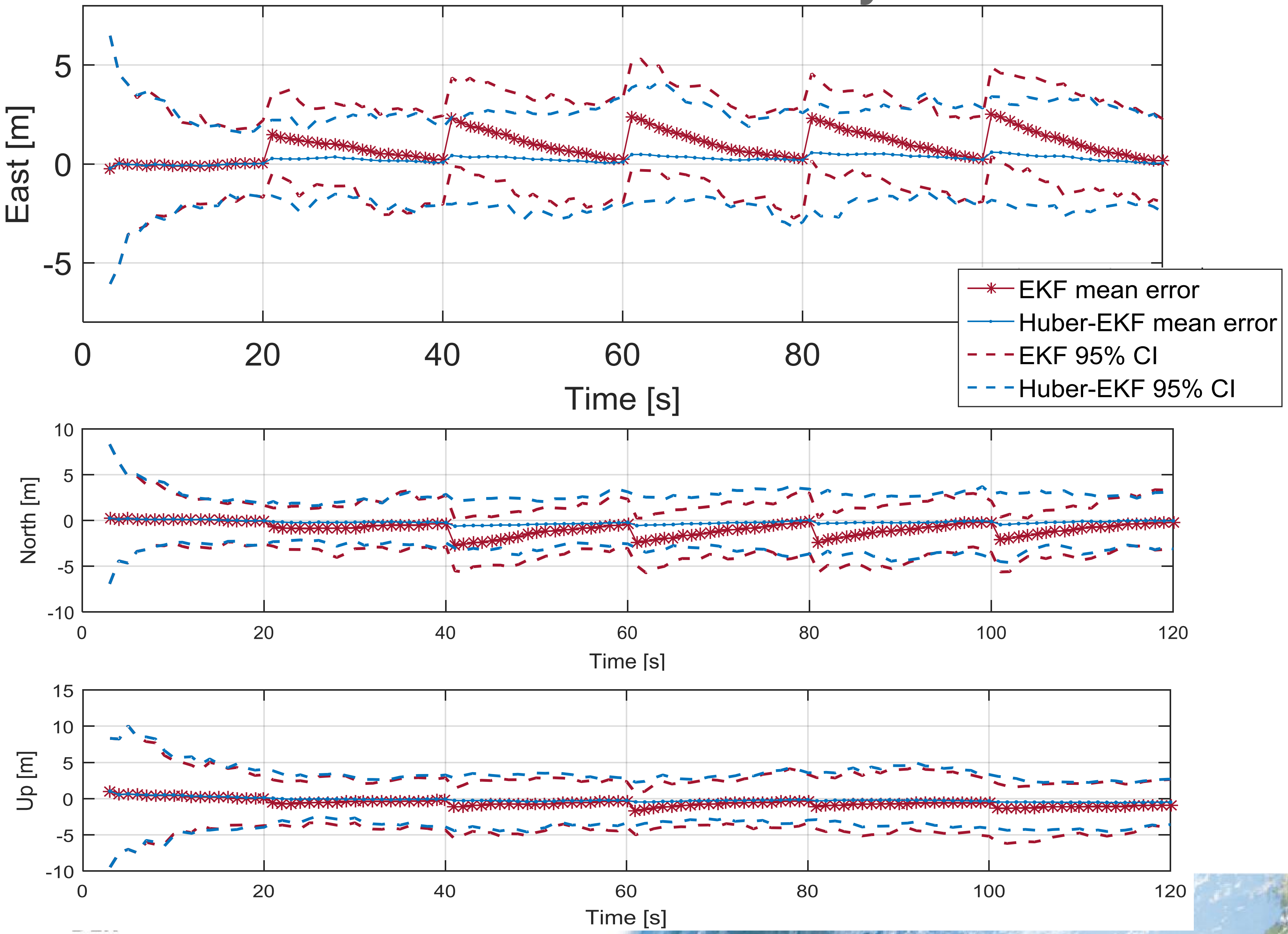
- Pseudoranges and Inertial measurements (specific forces & turn rates):
  - Pseudorange simulated sigma: 5 meters
  - Inertial Grade: Tactical

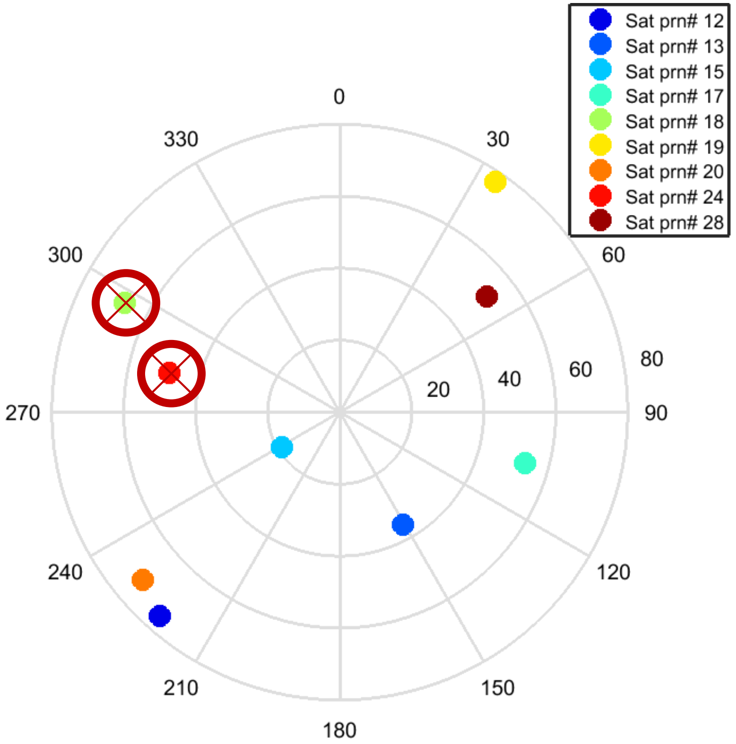
Results: Nominal Scenario, Covariance Differences





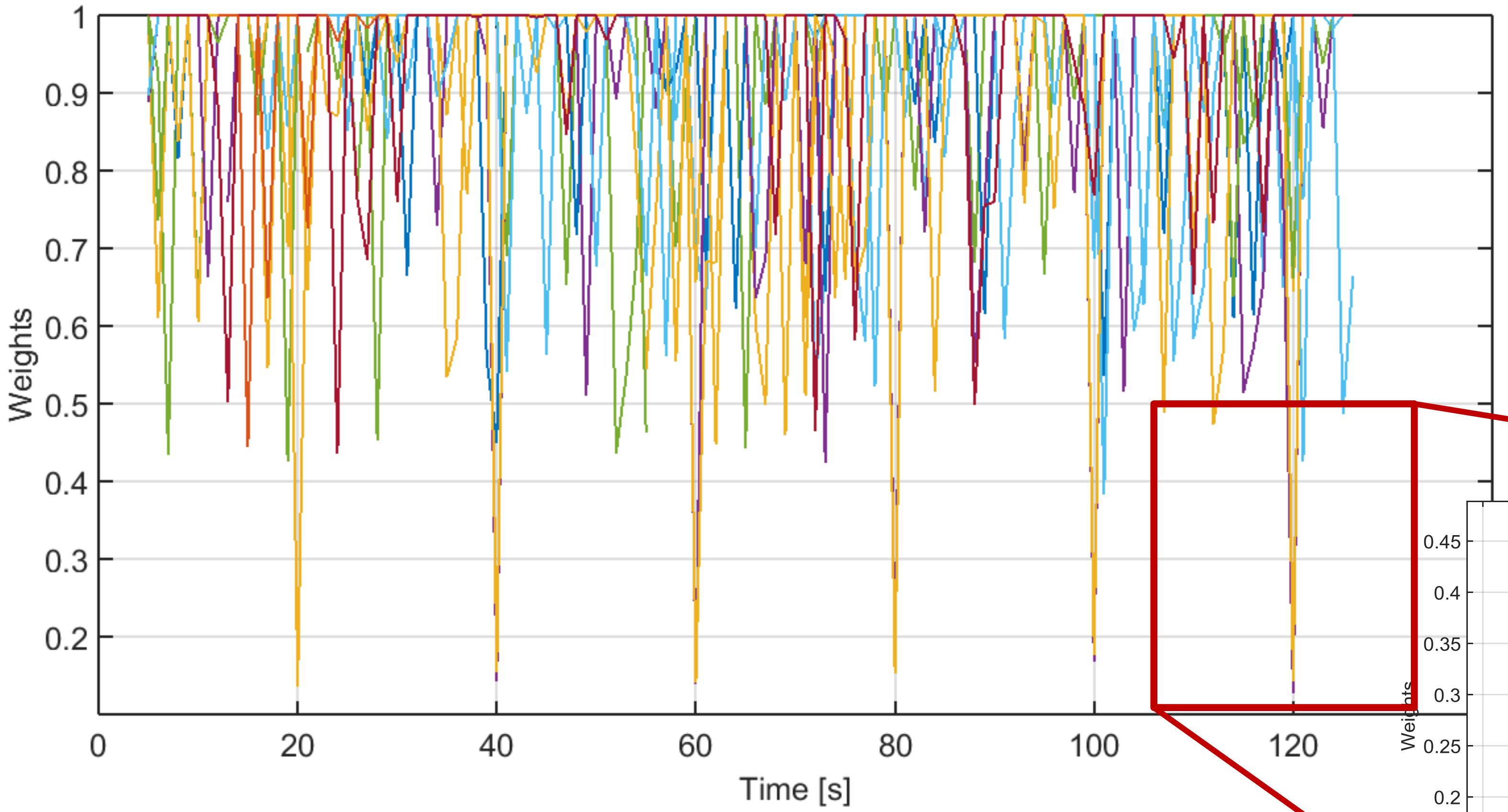
Results: Performance under 2 faulty measurements

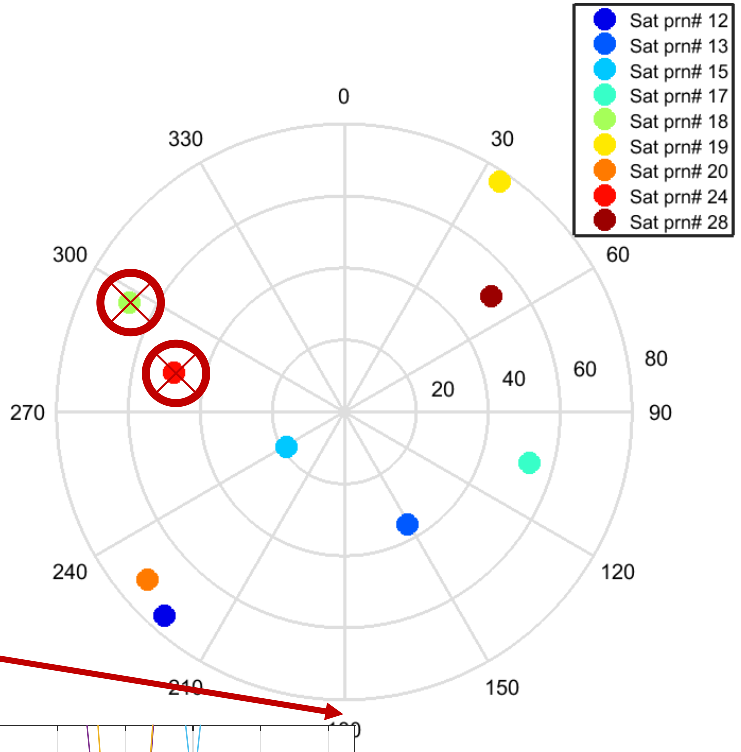


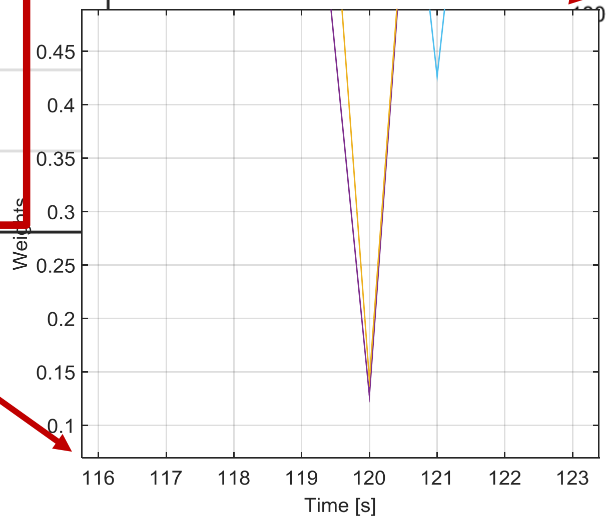


- 100 Monte Carlo Simulations
- Inject bias faults of 40 meters in selected satellites every 20 seconds
- Results:
  - Mean error
  - 95% CI

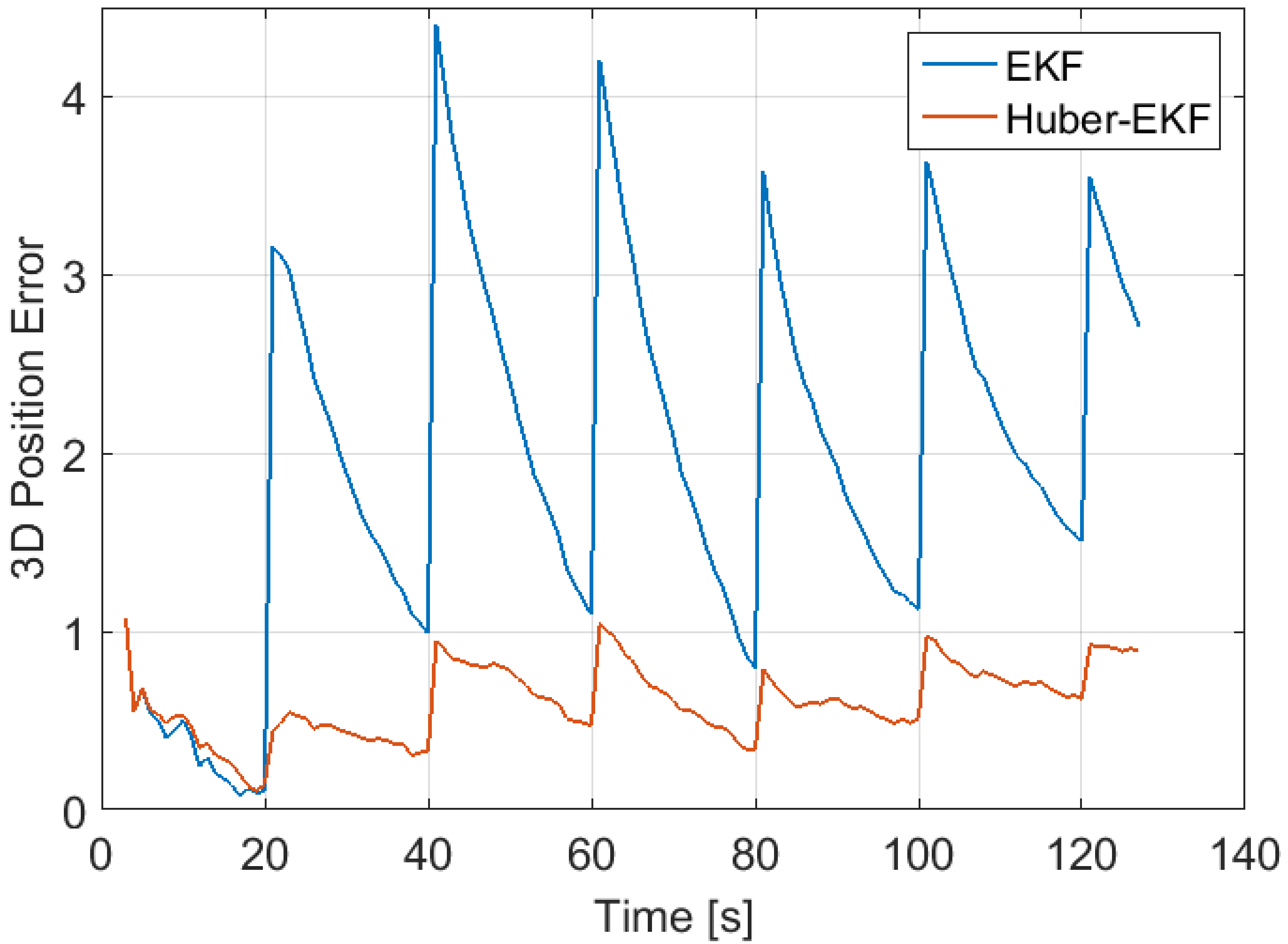
Results: Weight Evolution (2 Faults)

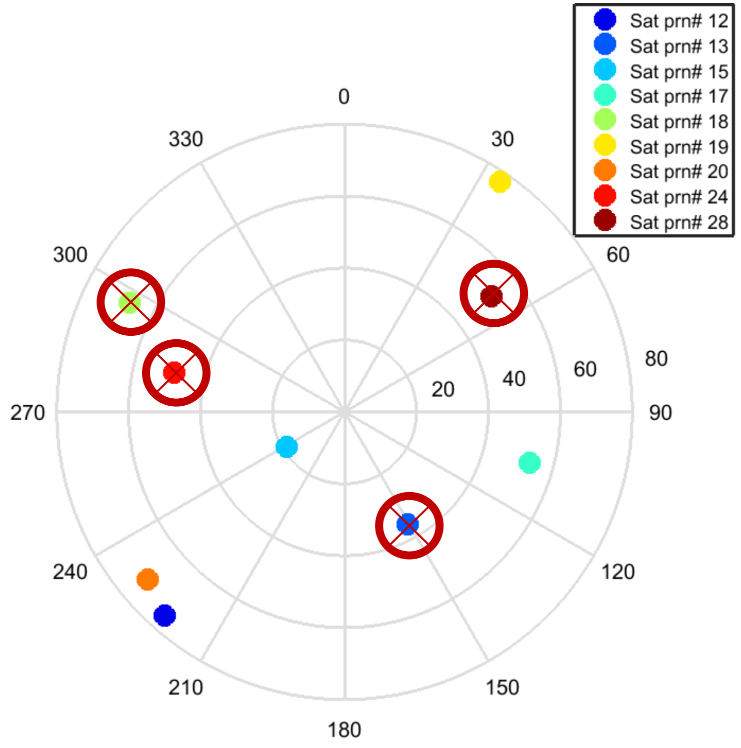






Results: Performance under 4 faulty measurements





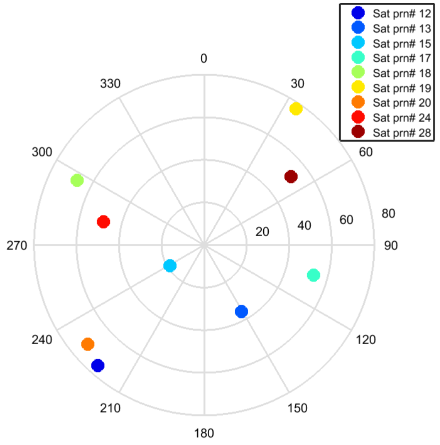
- 100 Monte Carlo Simulations
- Inject bias faults of 40 meters in selected satellites every 20 seconds
- Results:
  - 3D position error

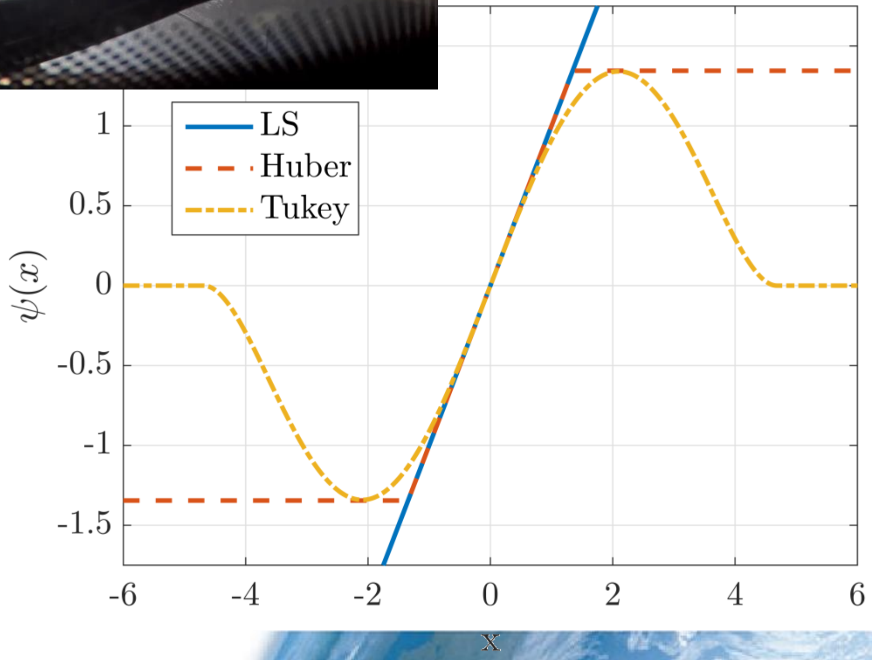
Conclusions & Outlook

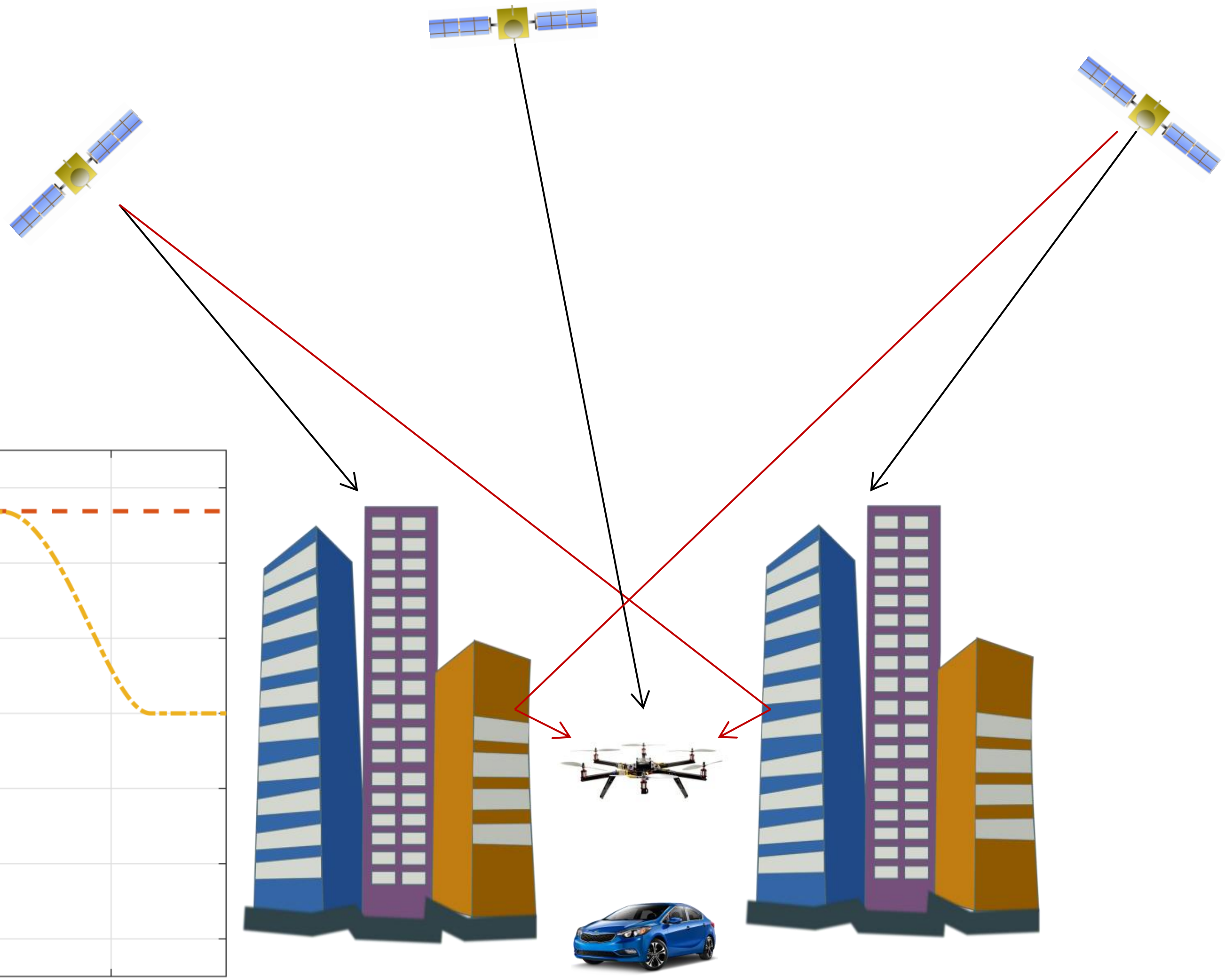
- Robust estimators are promising alternative to existing resilient algorithms, in particular for land-based applications
- Robust EKF is slightly sub-optimal
- Huber EKF is more resilient against multiple faults compared to normal EKF
- The use of inertial suggest improvement deweighting capability

- Outlook:
  - Further Simulations with other Robust estimators
  - Comparison with linear estimator + FDE
  - Testing with real measurements

Thank you







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